Advanced Processing for High Frequency Active Systems

Christian G. Hempel, Ph.D.
Sensors and Sonar Systems Department, Code 1522
Naval Undersea Warfare Center
1176 Howell Street
Newport, RI 02841
phone: (401) 832-8648 fax: (401) 832-2757 email: hempelcg@npt.nuwc.navy.mil

Mr. Stephen G. Greineder
Sensors and Sonar Systems Department, Code 159B
Naval Undersea Warfare Center
1176 Howell Street
Newport, RI 02841
phone: (401) 832-8238 fax: (401) 832-2757 email: greinedersg@npt.nuwc.navy.mil

Award Number: N0001407WX20783

OBJECTIVES

The purpose of the effort reported here is to investigate advanced signal processing and modern multi-target batch tracking algorithms for high frequency active applications. High frequency active sensor systems are currently being evaluated by the Navy to meet the Sea Power 21 Sea Shield objectives for force protection and port security. These systems have elementary baseline signal processing and tracking capabilities and could benefit from incorporating advanced acoustic processing and multi-target tracking algorithms designed for distributed active sensors. The incorporation of an improved processing is aimed at reducing the high rate of false tracks being reported during system testing. This effort used active measurements from prototype actve sonar sensors to demonstrate false alarm reduction and multi-target tracking on structured test data provided by ARL/UT, assess overall tracking performance and identify areas requiring algorithm improvements.

APPROACH

The results of a previous investigation showed that a modern batch type tracking algorithm will provide improved tracking performance over conventional recursive tracking methods. In that study the Probabilistic Multi-Hypothesis Tracking (PMHT) algorithm was manually initialized to expedite the comparison of the recursive baseline tracker and the batch PMHT method. Consequently, in FY07 effort was devoted to devising, implementing, and testing an appropriate automated track initialization method based on the Hough transform and a statistical test.

For discrete data (e.g., sonar echoes), the Hough transform is a histogram version of the discrete Radon transform where the data are partitioned into sets of non-overlapping bins at various angles that represent different possible target track trajectories [1]. Figure 1 depicts a set of Hough bins at a single angle for the one-dimensional tracking problem.

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
30 SEP 2007	**Annual**	**00-00-2007 to 00-00-2007**

4. TITLE AND SUBTITLE
Advanced Processing For High Frequency Active Systems

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Undersea Warfare Center,Sensors and Sonar Systems Department, Code 1522,1176 Howell Street,Newport,RI,02841

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR’S ACRONYM(S)

11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
code 1 only

14. ABSTRACT
The purpose of the effort reported here is to investigate advanced signal processing and modern multi-target batch tracking algorithms for high frequency active applications. High frequency active sensor systems are currently being evaluated by the Navy to meet the Sea Power 21 Sea Shield objectives for force protection and port security. These systems have elementary baseline signal processing and tracking capabilities and could benefit from incorporating advanced acoustic processing and multi-target tracking algorithms designed for distributed active sensors. The incorporation of an improved processing is aimed at reducing the high rate of false tracks being reported during system testing. This effort used active measurements from prototype actve sonar sensors to demonstrate false alarm reduction and multi-target tracking on structured test data provided by ARL/UT, assess overall tracking performance and identify areas requiring algorithm improvements.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**Same as Report (SAR)**	**15**	

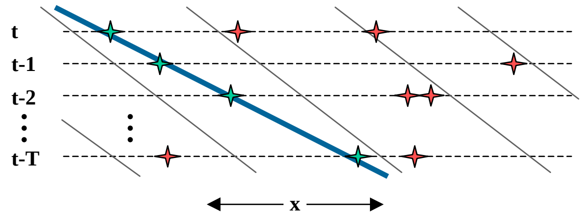

Figure 1. Example of Hough transform-style bins. Parallel slanted lines represent the boundaries; stars represent data points in x-space at each time scan; and the thick line, through four points, represents how a true target trajectory might fall within the bin.

An appropriate test statistic must be defined and applied to the data in each bin. A test statistic based on the Hough transform values (i.e., the total number of echoes in each bin) has been suggested by Luginbuhl, Sun, and Willett [2]. Their test, however, does not take into account the temporal structure of the data in each bin and thus requires many pings of data to accumulate before good results may be obtained. A straightforward generalization of their test is the so called "M of N" test which requires at least M (e.g., 5) detections in N (e.g., 6) consecutive cells of a Hough bin to initialize a track. Moreover, in this application the M detections are required to be in separate Hough cells to prevent a single high clutter ping from initializing an avalanche of false tracks.

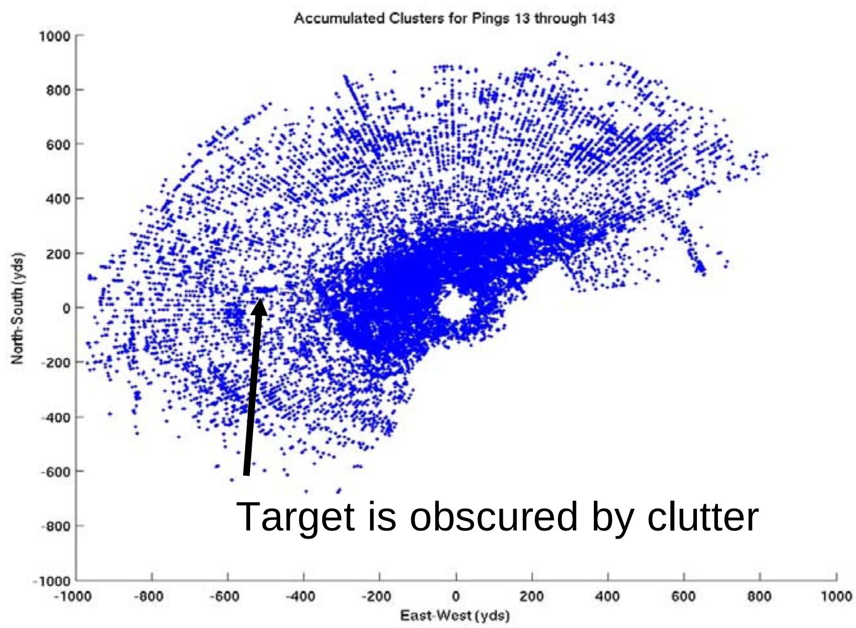

Figure 2. Clustered detections from baseline processing shown in blue. Target is detected but is indistinguishable from clutter.

A preliminary study showed that the clutter density in the baseline cluster data is computationally overwhelming for the Hough bin based track initialization described above. Moreover, in order to detect targets of interest the false track initialization rate was orders of magnitude greater than desired. Figure 2 shows the total set of clustered detections obtained from 130 pings of test data. Most of the clutter arises from fixed scatterers in the search region. Since the sonar

system of interest is active, mono-static and the sensor is anchored the background should change very slowly over time. Thus, effort was directed at developing a method that would automatically suppress the returns of fixed objects and pass the returns of moving objects. A normalizer was devised that estimates the background level, $s(r,\theta,t)$, for each data sample, $f(r,\theta,t)$, in the current ping by averaging the data samples at the same range and bearing from some number of prior pings after an appropriate gap, *d*;

$$s(r,\theta,t) = \frac{1}{N}\sum_{n=1}^{N} f\left(r,\theta,t-d-n\right)$$

Each sample of data in the current ping is then divided by its corresponding background noise estimate to produce the normalized data, $\tilde{f}\left(r,\theta,t\right)$.

$$\tilde{f}(r,\theta,t) = \frac{f(r,\theta,t)}{s(r,\theta,t)},$$

The purpose of the gap, *d*, is to allow sufficient time for the detections of moving objects of interest in the data used to estimate the background to be in a different location from the current scan.

In order for the time average normalization to be effective the data must be registered to a common frame of reference. Although the sensor is anchored and therefore geographically fixed it often slowly rotated from ping to ping causing to the background to appear to rotate in the opposite direction. For the time average normalizer to be effective the data must be stabilized for sensor rotation, otherwise the background noise estimates will be misaligned with the current ping which will allow more false detections and may reduce the probability of detecting the target. Moreover, uncompensated sensor rotation will increase the error in the bearing measurements for targets of interest which will reduce tracking performance. The sensor heading information along with a simple interpolation scheme based on the FFT was used to compensate for ping to ping sensor rotation. The availability of accurate sensor heading values is essential to this method; inaccurate sensor heading values cause the data from multiple pings to be misaligned which degrades the performance of the normalizer and tracking functions.

FY06 WORK COMPLETED

Task 1: Developed automated track initialization algorithm.

Task 2: Developed time averaging normalizer and data registration methods.

Task 3: Prototyped candidate processing algorithms in MATLAB.

Task 4: Demonstrated performance of algorithms prototype on sea trial data.

RESULTS AND CONCLUSIONS

A set of 14 structured test runs collected on a prototype monostatic system was provided by ARL/UT to evaluate the processing and tracking performance of the candidate algorithms. The data sets consist of multiple runs differing in the contact type (surface/sub-surface). For the subsurface contacts there were two different configurations of the contact. Each data set consists of, among other information, range, bearing, and amplitude clusters representing both targets, interference and clutter (returns due to random background noise, returns from stationary objects, etc.). For each run, the range and bearing values of each clustered detection were converted to Cartesian coordinates to match the assumptions of the tracking algorithm.

When the data could be accurately registered the time averaging normalizer suppresses almost all clutter from fixed scatterers in the search region. A region of high clutter due to fish and near field volume reverberation near (i.e., within 250 yards) the sensor remains. Targets of interest outside the near field volume reverberation region are clearly evident in the data; operators could easily distinguish the targets. Moreover, for those data sets the track initialization and subsequent PMHTAS tracker easily tracked the targets; see figures 3, and 5 through 10. Targets of interest inside the near field volume reverberation are more difficult to distinguish from clutter and track; see figures 11, 12, and 14. Some data sets, however, could not be accurately registered; it appears the heading sensor values were inaccurate. In those data sets the normalizer did not sufficiently suppress the clutter; see figures 4, and 13 through 15.

The track initialization and tracking performance largely depended on the quality of the normalized data. If the data could be accurately registered and successfully normalized then the target could be easily tracked; see figures 16 through 19. Otherwise the track initialization was typically overwhelmed by the clutter and the tracking performance was significantly degraded, see figure 20.

These results clearly show that when the data from multiple pings can be accurately registered the clutter from fixed scatterers in the search region can be almost entirely eliminated without significantly reducing the probability of detecting targets of interest. Near the sensor a relatively small zone (approximately 6% of the total search region) of high volume reverberation is not eliminated by the new processing. The results also show that the errors in the heading sensor values will often be large enough to prevent accurate data registration. A data registration method that does not rely on accurate heading sensor values should be developed for this application. Since most operational areas will contain spatially varying bathymetry maximum likelihood estimation methods that exploit prominent fixed scatterers in the background can be used to determine the amount of sensor rotation between successive pings of data. Once the ping to ping sensor rotation is known interpolation algorithms can be used to compute beam data that can be processed by the time averaging nomalizer.

SUMMARY AND RECCOMMENDATIONS

In addition to the issues regarding data registration and normalization issues discussed above, more effort is clearly needed to incorporate appropriate classification features into the track initialization and tracking functions to further reduce the number of false tracks especially in the near field volume reverberation zone. Any further application of the candidate algorithms developed under

this effort to the high frequency active tracking problem should include the use of appropriate classification features. These and other recommended system and tracking related improvements are summarized in the list below.

- Develop data registration methods that exploit local bathymetry and do not rely on heading sensor values.
- Make the track initialization and tracking functions adaptive to the level of clutter in the near field volume reverberation zone.
- Incorporate automated track maintenance (e.g., eliminating redundant tracks, track declaration) methods into the tracking function.
- Develop and incorporate appropriate classification feature models (e.g., amplitude or highlight structure) into the track initialization and tracking functions.
- Utilize Doppler sensitive waveforms in specific applications.
- Include thorough truth and reconstruction information in all future data driven analyses.

RELATED PROJECTS

- There is a related effort being conducted at NRL to develop a physical understanding of the expected high frequency returns from the contacts used in this investigation. This information could form the basis for robust classification and be directly inserted into the tracker data association stage to eliminate clutter measurements.
- There is an ongoing effort funded by PMS 480 to understand the present capabilities of proposed automated high frequency active tracking systems. Advances from this effort could be applicable to issues identified by the current effort.

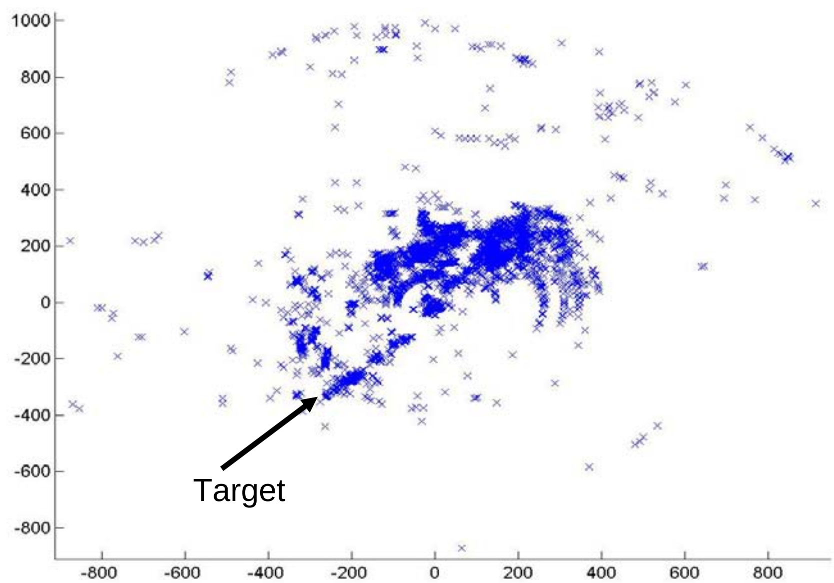

Figure 3. Subsurface Contact (configuration 1) run 2. Cluster data is shown in blue. Clutter from stationary satterers is well suppressed and the target is clearly evident.

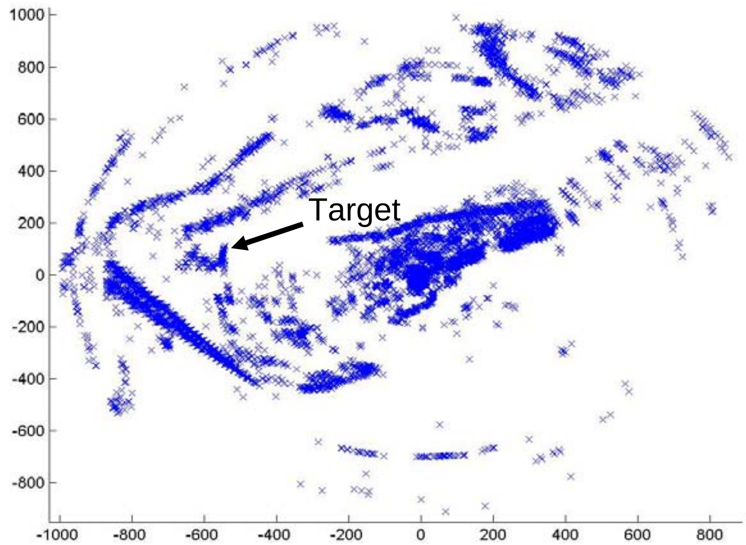

Figure 4. Subsurface Contact (configuration 1) run run 5A. Cluster data is shown in blue. Clutter is poorly suppressed. The target is detected but is indistinguisable from clutter.

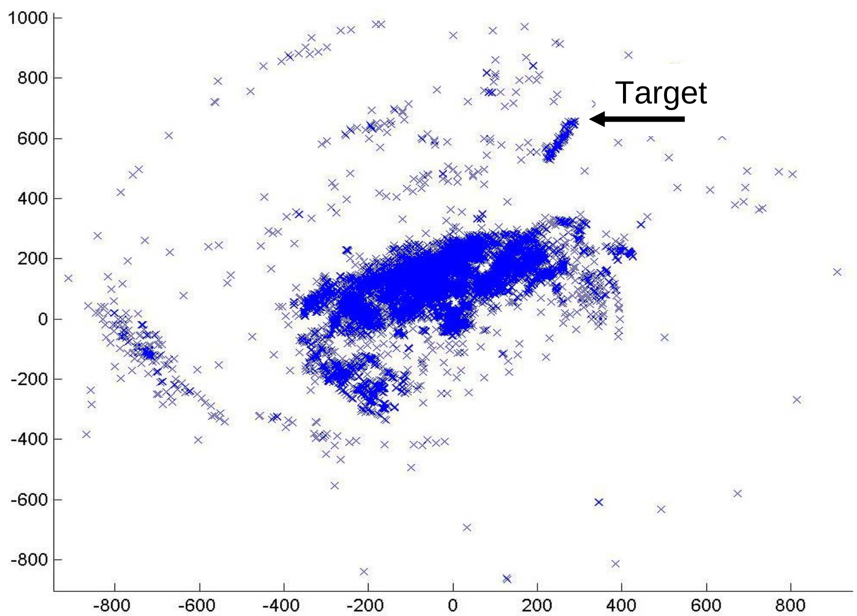

Figure 5. Subsurface Contact (configuration 1) run 10. Cluster data is shown in blue. Cluttter from fixed scatterers is well suppressed and the target is clearly evident.

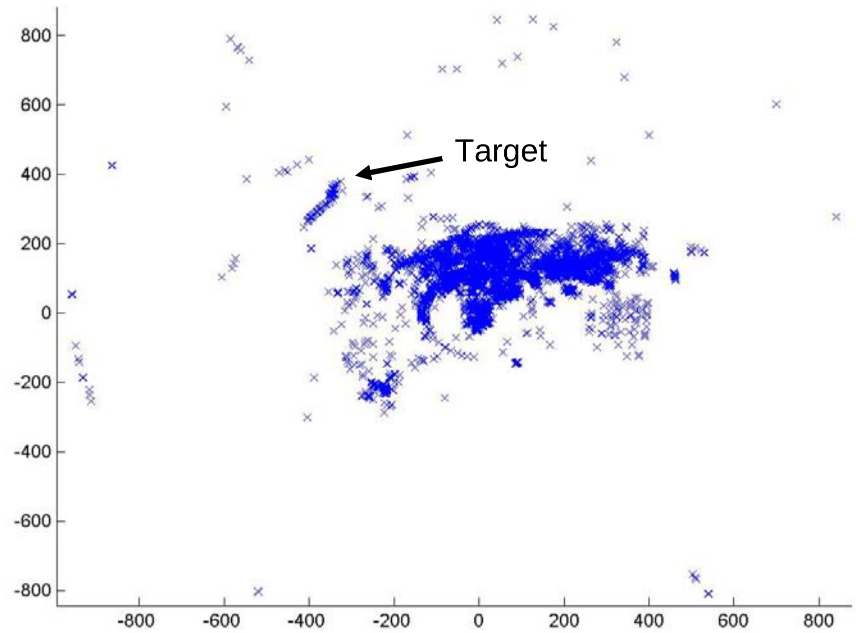

Figure 6. Subsurface Contact (configuration 1) run 14. Cluster data is shown blue. Cluttter from fixed scatterers is well suppressed and the target is clearly evident.

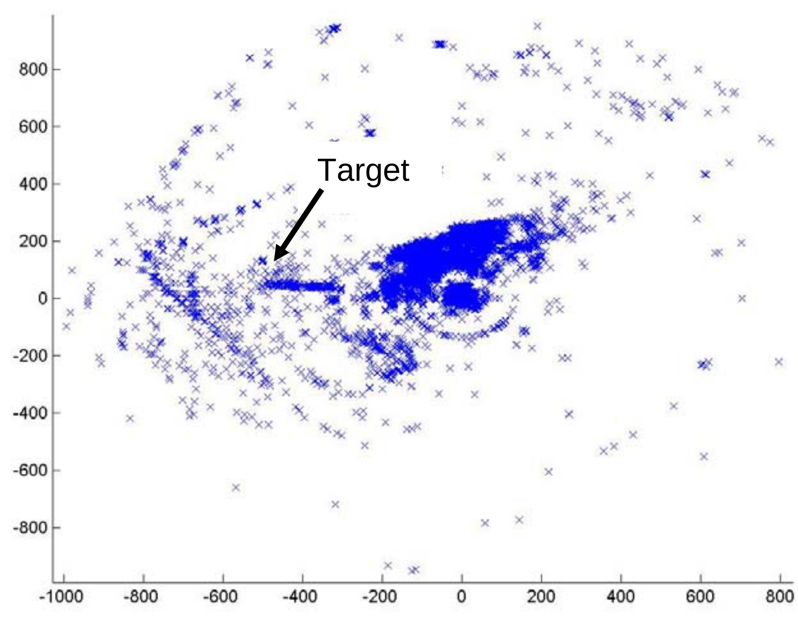

Figure 7. Subsurface Contact (configuration 2) run 2. Cluster data is shown in blue. Clutter is moderately suppressed. The target is clearly evident and distinguishable from the clutter.

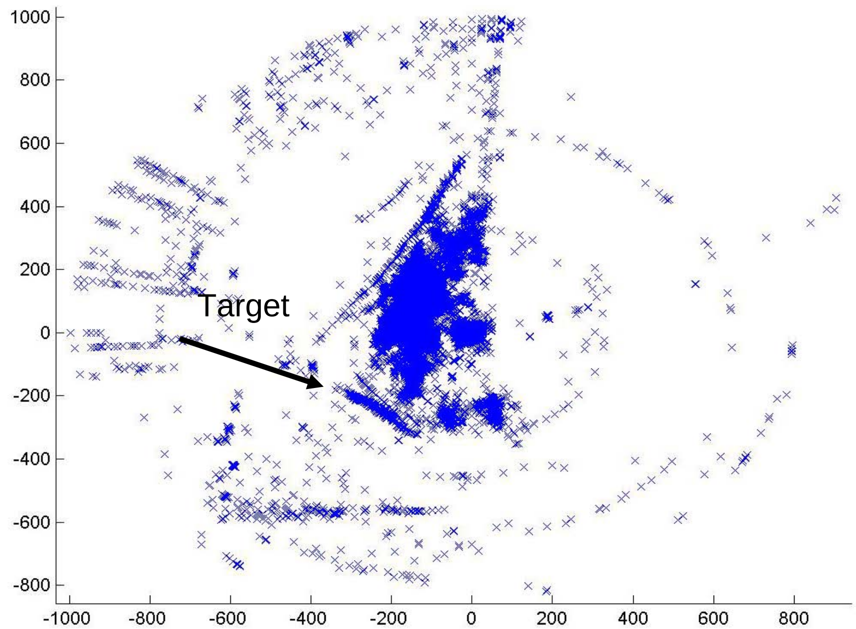

Figure 8. Subsurface Contact (configuration 2) run 5. Cluster data is shown in blue and is rotated counter clockwise. Clutter from fixed scatterers is moderately suppressed. The target is clearly evident and distinguishable from the clutter.

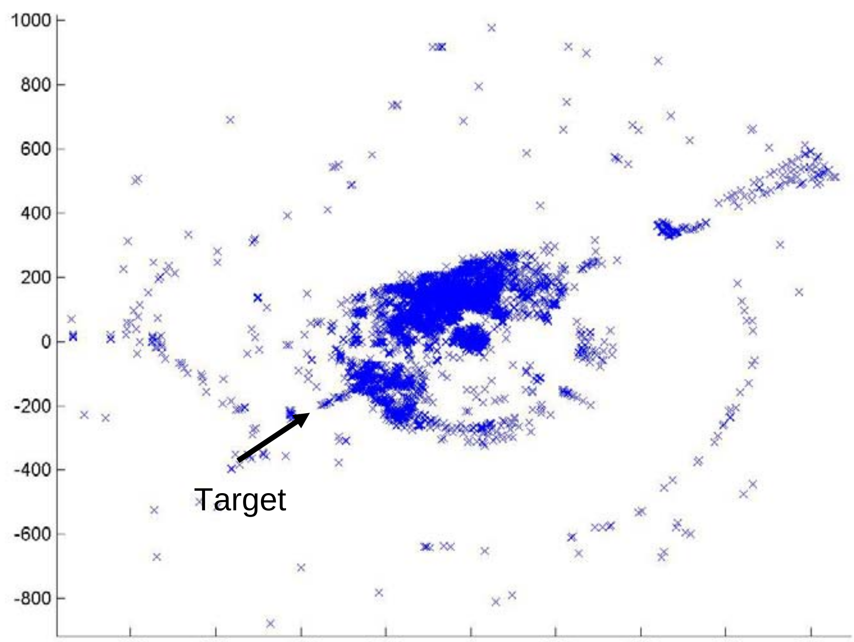

Figure 9. Subsurface Contact (configuration 2) run 13. Cluster data is shown in blue. Clutter from fixed scatterers is well suppressed. Target is detected and initially is distinguishable from near field volume reverberation.

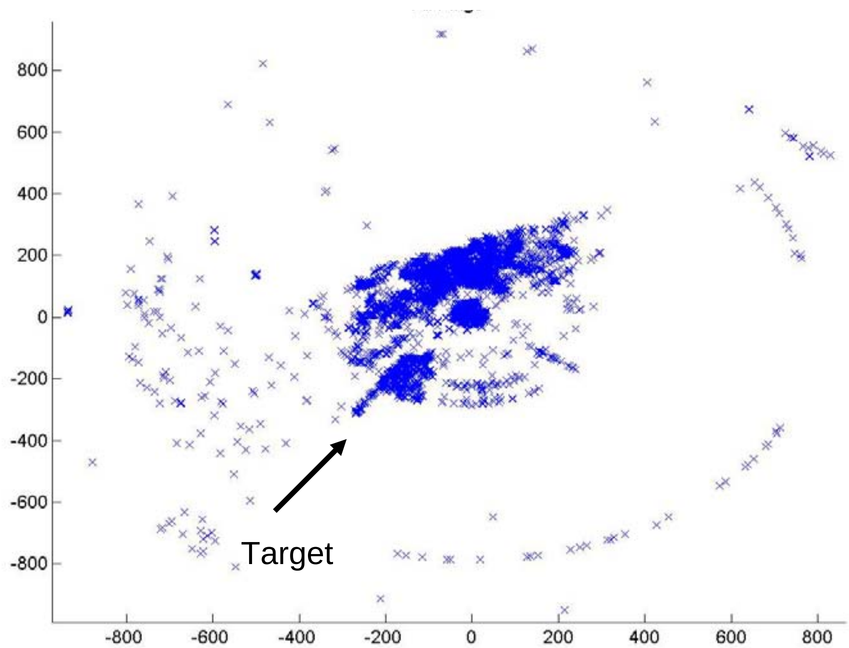

Figure 10. Subsurface Contact (configuration 2) run 14. Cluster data is shown in blue. Clutter from fixed scatterers is well suppressed. Target is detected and initially is distinguishable from nearfield volume reverberation.

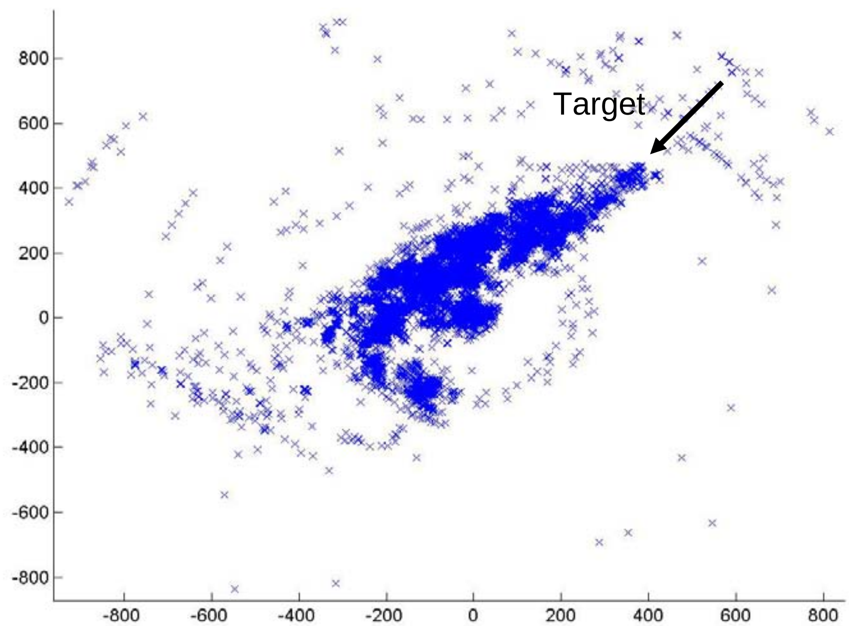

Figure 11. Subsurface Contact (configuration 2) run 10. Cluster data is shown in blue. Clutter from fixed scatterers is well suppressed. Target is detected but difficult to distinguish from near field volume reverberation

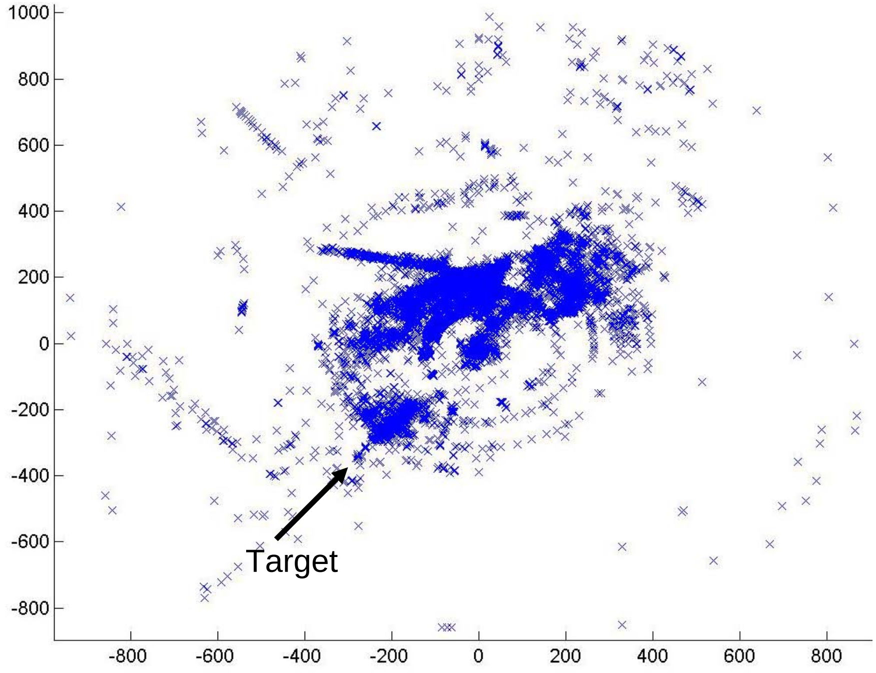

Figure 12. Surface contact run 2. Cluster data is shown in blue. Clutter from fixed scatterers is moderately suppressed. Target is detected but is indistingiushable from clutter and near field volume reverberation.

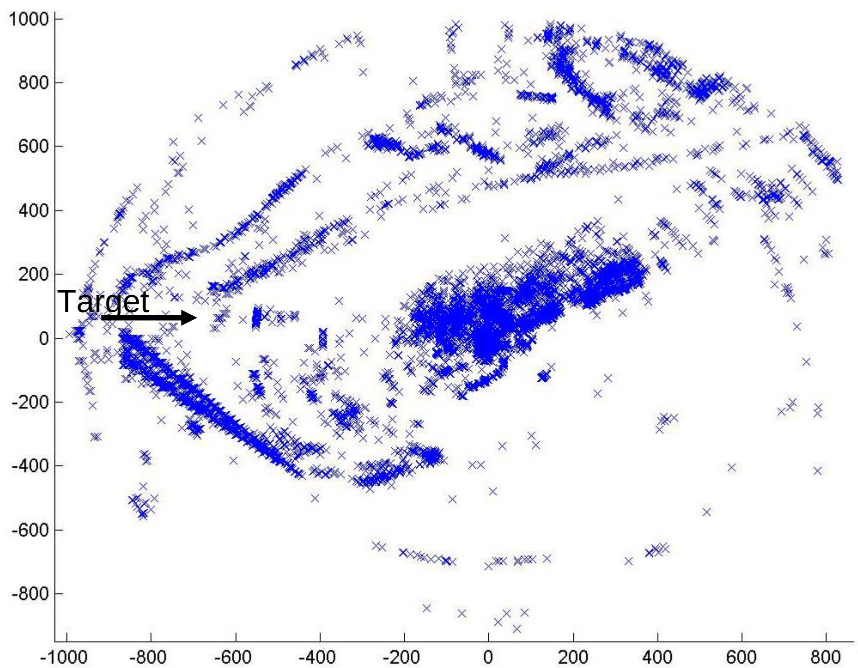

Figure 13. Surface contact run 5. Cluster data is shown blue. Clutter from fixed scatterers is poorly suppressed. Target is weakly detected and is inditinguishable from the clutter.

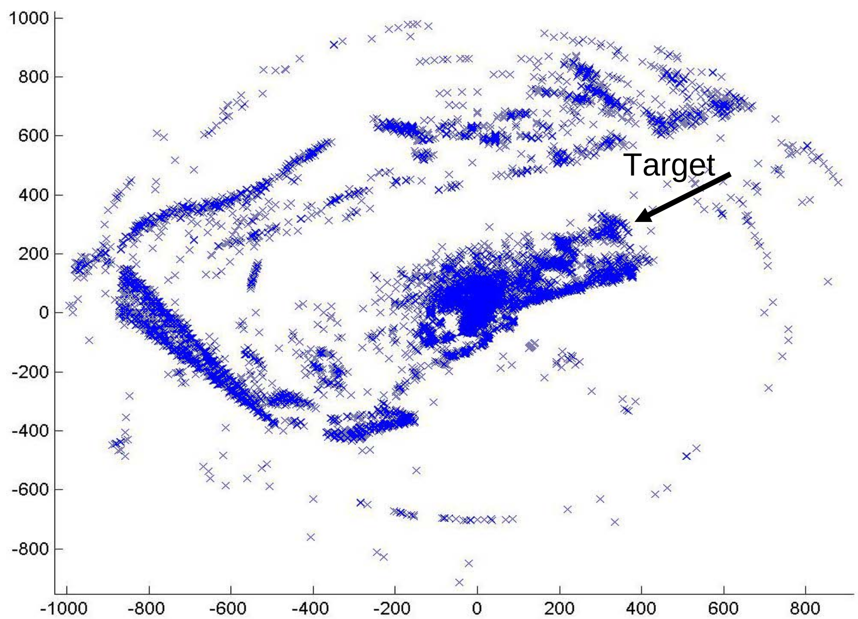

Figure 14. Surface contact run 11. Cluster data is shown in blue. Clutter from fixed scatterers is poorly suppressed. Target is clearly detected but is difficult to distinguish from clutter and near field volume reverberation.

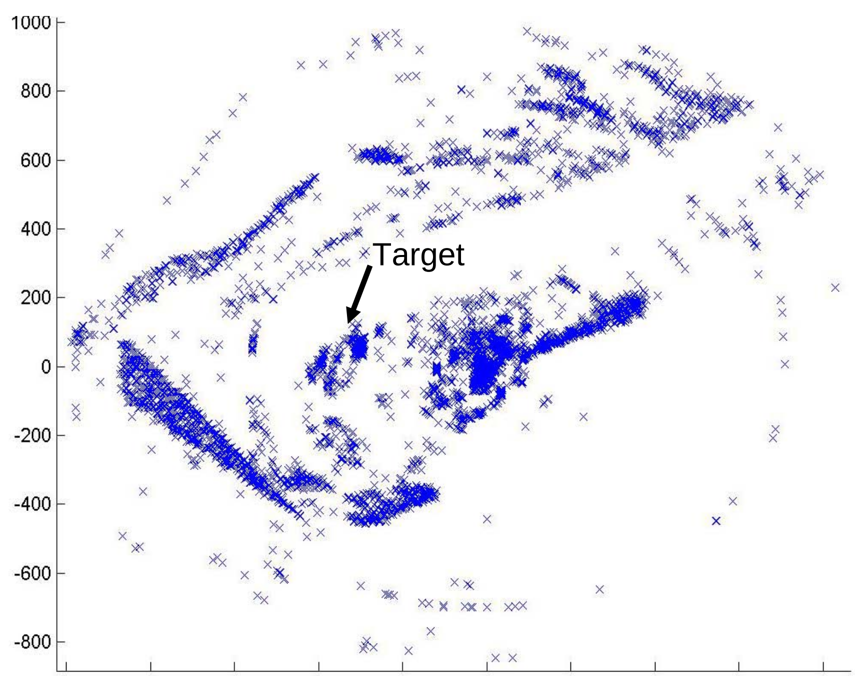

Figure 15. Surface contact run 13a. Cluster data is shown in blue. Clutter from fixed scatterers is poorly suppressed. Target is weakly detected and indistinguishable from the clutter.

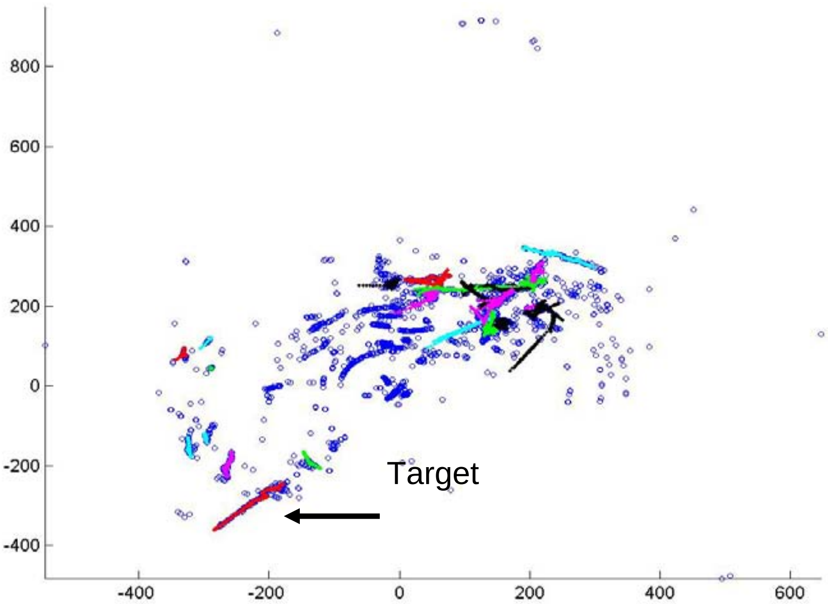

Figure 16. Subsurface Contact (configuration 1) run 2. Cluster data is shown in blue. Clutter from stationary satterers is well suppressed and the target is easily tracked.

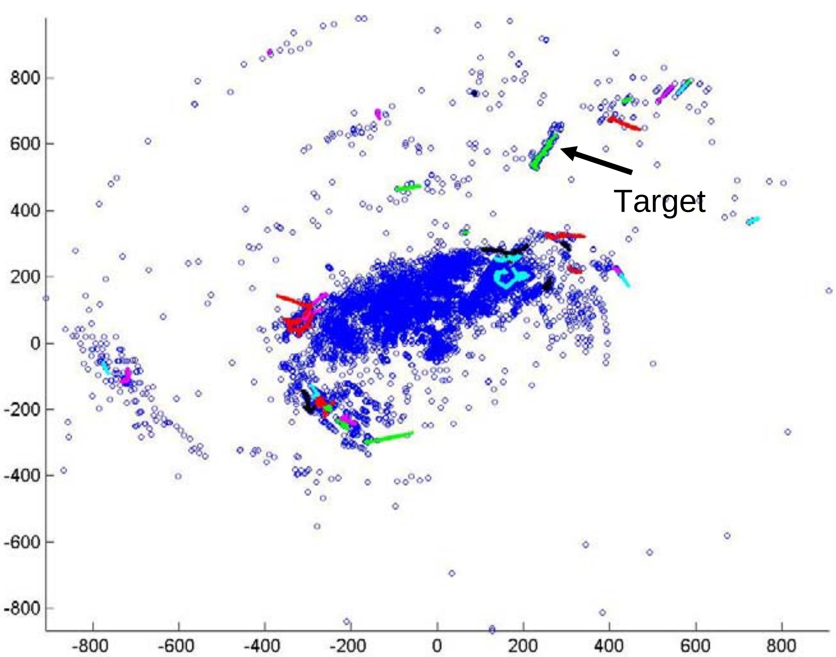

Figure 17. Subsurface Contact (configuration 1) run 10. Cluster data is shown in blue. Cluttter from fixed scatterers is well suppressed and the target is easily tracked.

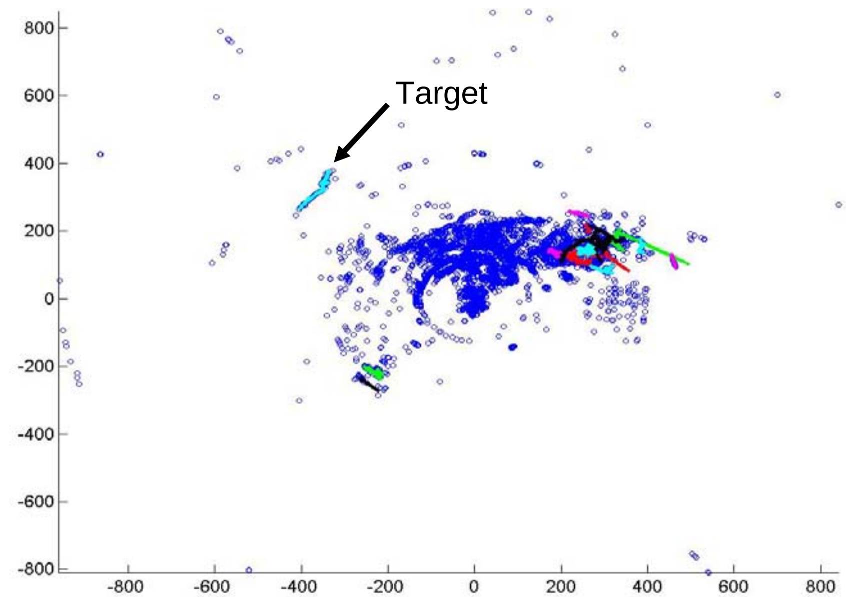

Figure 18. Subsurface Contact (configuration 1) run 14. Cluster data is shown blue. Cluttter from fixed scatterers is well suppressed and the target is easily tracked.

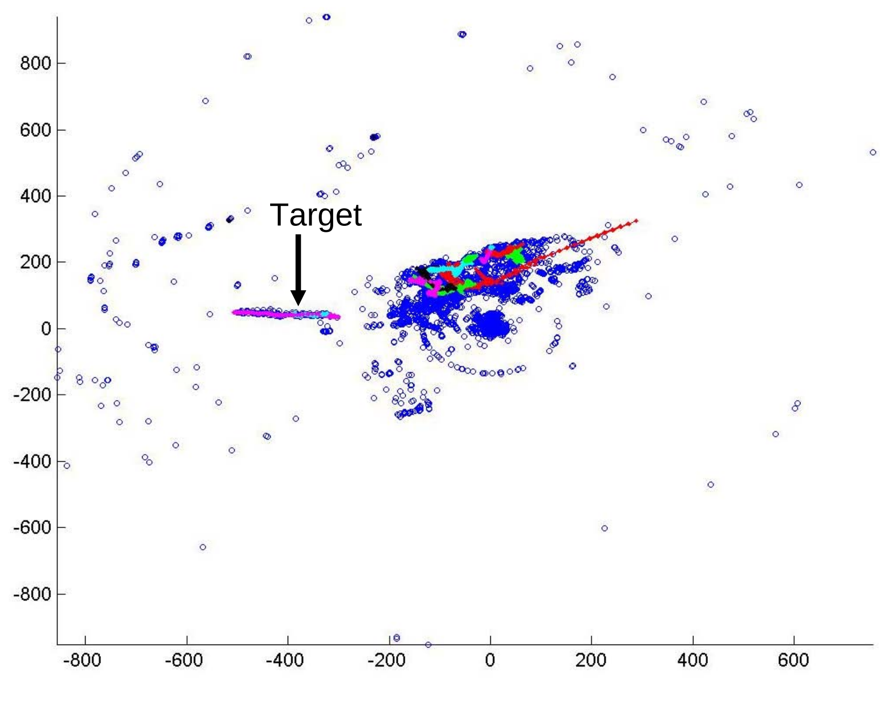

Figure 19. Subsurface Contact (configuration 2) run 2. Cluster data is shown in blue. Clutter is moderately suppressed. The target is clearly distinguishable from the clutter and easily tracked.

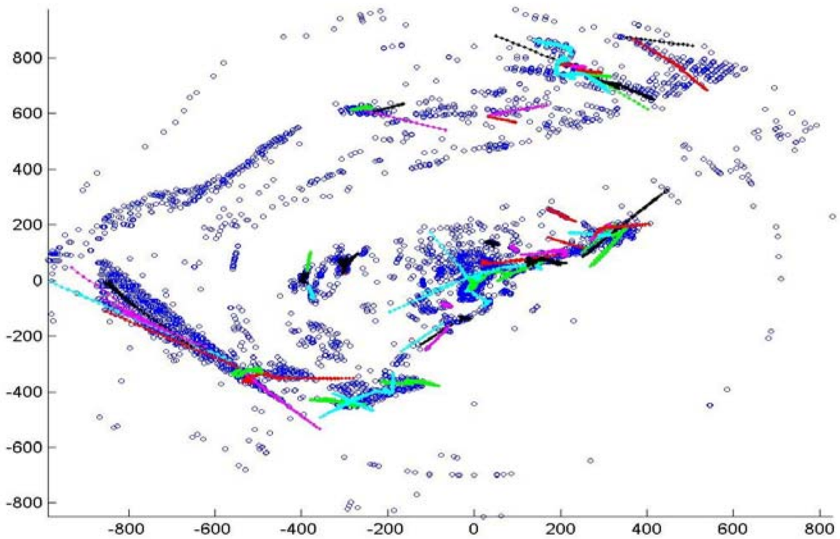

Figure 20. Surface Contact run 13a. Cluster data is shown in blue. Clutter is poorly suppressed. The target is indistinguishable from the clutter and cannot be tracked.

IMPACT/APPLICATIONS

With increased emphasis on the use of active sonar for port protection, demonstration of the value added by the improved data registration and normalization is expected to transition to appropriate fielded systems.

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